An optimized approach for extensive segmentation and classification of brain MRI

Harish S.[1], G. F. Ali Ahammed[2]
[1]Visvesvaraya Technological University (VTU) Belagavi, India
[2]Visvesvaraya Technological University (VTU) PG-Center, India

Article Info

Article history:

Received Jun 13, 2019
Revised Oct 1, 2019
Accepted Nov 29, 2019

Keywords:

Brain tumor
Classification
Identification
Magnetic resonance imaging
Segmentation

ABSTRACT

With the significant contribution in medical image processing for an effective diagnosis of critical health condition in human, there has been evolution of various methods and techniques in abnormality detection and classification process. An insight to the existing approaches highlights that potential amount of work is being carried out in detection and segmentation process but less effective modelling towards classification problems. This manuscript discusses about a simple and robust modelling of a technique that offers comprehensive segmentation process as well as classification process using Artificial Neural Network. Different from any existing approach, the study offers more granularities towards foreground/ background indexing with its comprehensive segmentation process while introducing a unique morphological operation along with graph-believe network for ensuring approximately 99% of accuracy of proposed system in contrast to existing learning scheme.

Copyright © 2020Institute of Advanced Engineering and Science.
All rights reserved.

Corresponding Author:

Harish S.,
Visvesvaraya Technological University (VTU) Belagavi,
Belgaum, Karnataka 590018, India.
Email: harishsrinivasaiah@gmail.com

1. INTRODUCTION

Medical image processing has potential contribution towards diagnosing critical illness. Out of all the disease condition, brain tumor is considered as one of challenging state of illness which is also difficult to accurately diagnose [1]. Basically, brain tumor is represented by abnormal progress of carcinomic cells which could be either life threathening (malignant) or non-dangerous (benign). Therefore, it is essential to identify the malignant state before even it occurs [2-3]. At present, the healthcare sector employs three schemes to diagnose the state of criticality viz. i) computed tomography (CT-scan), ii) Magnetic Resonance Imaging (MRI), and iii) Biopsy. Basically, the first two diagnosis processes are non-invasive and uses medical imaging while the third process is surgical. Magnetic Resonance Imaging (MRI) is one of the dominant medium of diagnosing the abnormalities present in human body [4]. Brain is considered as one of the essential as well as complex human organ where diagnosis of the abnormalities are bit challenging. The challenge factor involved in diagnosis through brain MRI is the presence of various artifacts e.g. noise, inferior contrast, absence of ridges, frequent adoption of the supervised techniques, etc. Such problems are anticipated to be solved by medical image processing techniques. At present, there has been various researches focused towards proper identification of abnormalities present in brain as well as there is certain degree of work towards solving classification problems also [5-7]; however, they are also associated with significant amount of problems too which are quite hard to solve. A closer look into the quantity of the research work towards brain MRI shows that there are more number of works towards detection problem and little focuses on the classification problem. The prime reason behind this problem is that existing system doesn't offer extensive and, comprehensive extraction of significant features. This causes the system to deplete important set of clinical information which is predominantly required for making decision of the presence of abnormalities present in the brain MRI image. Apart from this, existing segmentation process are too straight forward and less work are found to be extensive [8, 9]. It has been seen that there has been not much focus toward employing pre-processing techniques much for brain MRI images, which is highly essential. If the pre-processing is not carried out than image quality of the brain MRI cannot be upgraded as well as the image components will have poor visual appearance. Apart from this, the clarity of the input image will not be good which will act as an impediment towards the further analysis process. Existing segmentation techniques are more focused on background factor and not much on the foreground, which is also one of the possible reason impacting on the accuracy. Therefore, this manuscript presents a framework which offers a comprehensive segmentation that acts as a compliment towards feature extraction too.

The background, this section is the extension of the brief review of the study towards brain MRI [10]. Study towards identifying complicated state of disease of brain was discussed by Huang et al. [11] where the authors have used kernel-based learning approach for assisting in classification. Kermi et al. [12] have presented multi-stage segmentation method over three dimensional input image of brain MRI. Usage of random forest over the active contours with multiple patches has been presented in the work of Ma et al. [13] for enhancing the segmentation technique. The implementation of linearized discriminant analysis is found in Wang et al. [14] for functional MRI which brings significant classification accuracy. Yuan et al. [15] have discussed about multi-center brain MRI classification by using convolutional neural networks (CNN) approach and obtained 92% of classification accuracy for large MRI dataset. A work of Zhan et al. [16] has discussed Glioma segmentation mechanisms by using multiple classifier based collaborative training. Literature has also witnessed usage of feature extraction along with learning approach method for assisting classification of brain as seen in the work of Gumaei et al. [17].

A hybrid form of feature extraction scheme has been introduced targeting for higher accuracy factor. The extreme learning technique was used for facilitating better form of classification technique. Segmentation process for specific disease condition of brain was seen in work of Liu et al. [18] where linearized kernel was used for classification. The presented work emphasizes about segmenting sub-cortical region of brain using a specific image registration method as well as sparse classifier design that mechanizes kernel space of linearized form. The study uses probability concept for constructing structures and then it extracts the probable ridges of the brain. Similar direction of work was also carried out by Wang et al. [19]. The technique constructs a connected network formulated from the kernel technique of graph followed by computing the correlation for such networks. A unique work of Liu et al. [20] has presented the hierarchical brain networks for classification of structural MRI by using schizophrenia based method. Similar kind of research with different approaches are found in Kaur et al. [21], Kasobov et al. [22, 23], Aemananzas et al. [24], Liu et al. [25, 26] etc. The works of Kaur et al. [21] have focused on classified the gliomapart of the brain using ensemble decomposition technique along with the presence of the adaptive noise.

The work of Kasobov et al. [22, 23] have worked on classification of brain data considering its spatio-temporal aspect followed by applying machine learning of dynamic order specific to a particular part of brain region. The approach presented by Aemananzas et al. [24] has used voxel-based concept using ensemble classifier while Liu et al. [25, 26] have used hierarchical network with labeling mechanism. Most recently, the work of Mallick et al. [27] have presented a classification scheme using neural network and wavelet based approach over brain MRI. The technique reduces the number of fundamental features with enhanced decomposition characteristics. Shao et al. [28] have carried out segmentation process in order to identify specific region of brain for facilitating classification process. Study using segmentation was also carried out by Wang et al. [29] where the authors have used convolution neural network for better accuracy. The authors have performed segmentation of brain MRI image into essential clinical factors for internal diagnosis of the brain with usage of recursive blocks. The complete implementation was carried out over three dimensional MRI image of brain. Explicit discussion of the decomposition-based approaches was carried out by Gudigar et al. [30] for investigation classification performance for multiple classes of abnormalities of brain. The technique uses feature extraction for bispectral signals and integrated with supervised approach for projection of neighboring pixels. The study has used support vector machine for training and classification. From the extensive survey analysis, the research problem is formed with current state of art in the research domain. The next section briefs about problems being identified after reviewing the existing approaches.

The research problem, the significant research problems identified are as follows: The existing approaches has lesser emphasis on preprocessing which is essential to ensure better accuracy towards both detection and classification of brain MRI. The segmentation approaches of existing studies are too specific which is not capable of ensuring the comprehensive identification of dynamic states of background images.

There are less focus towards formulating a robust indexing mechanism for both foreground as well as background images which reduces the accuracy level of classification. Majority of the optimization technique are computational intensive process which significantly affects the decision making system while performing classification process. Therefore, there is a need of "*developing a robust segmentation as well as classification process towards performing comprehensive diagnosis of actual state of brain tumor from an MRI image is complex task*".

The proposed solution, developing an explicit process for ascertaining a better classification performance can be only implemented if the system possess more information about the features as well as comprehensive segmentation has been carried out. For this purpose, a system has been developed that performs an enhancement of the brain MRI image for multi-level enhancement. Considering that all the preliminary artifacts are addressed and eliminated, the proposed system is now ready to take the input of the pre-processed brain MRI image. The present work introduces a framework that is capable of performing non-conventional segmentation of the brain MRI image. The adopted scheme is shown in Figure 1.

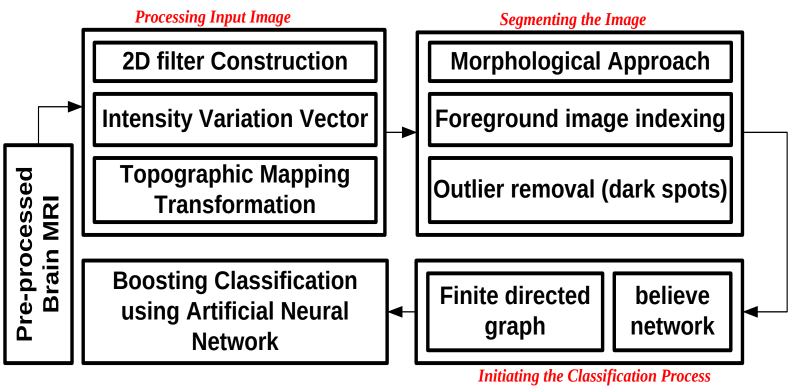

Figure 1. Undertaken scheme of proposed classification

The complete system offers a comprehensive segmentation process which acts as a compliments towards the classification process too. The input image is basically a pre-processed image obtained from [31] which undergoes 4 different rounds of operation viz. processing input image, segmenting image initiating the classification process, and applying neural network. The first level of the segmentation is carried out on the basis of the fluctuation of the intensity factor of the input brain MRI image while the second level of segmentation is carried out on the basis of the the topographic mapping transformation concept which converts the preliminary segmented image into various discrete topography. Such mapped topography facilitates toward offering more granularity in the diagnosis process with more user friendly visualization. Each processes are very much sequential which leads to explore more features which are numerically distinct for assisting in decision making process while performing training using neural network. The proposed system also introduces a unique segmentation process which facilitates in both foreground and background marking that is further subjected to believe network and finite directed graph before applying training using artificial neural network. Adoption of directed graph concept offers better structurization of the morphological elements obtained from the segmentation process which indirectly assists in the decision making process. Further adoption of believe network as well as histogram assists in confirming the decision of the region to be in normal or in abnormal state. The system also addresses the elimination of the outliers by truncating all the dark spots found in the process of classification. Further usage of artificial neural network offers an edge to the classification performance that leads to cost effective training process toward precise diagnosis of brain tumor. The next section elaborates about system implementation.

2. SYSTEM IMPLEMENTATION

The implementation of the proposed system is carried out in four sequential process viz. i) processing input image, ii) Segmentation of Image, iii) Initiating the classification process, and iv) Applying Artificial Neural Network. All the essential process are carried out considering brain MRI images. This section discusses about the strategies adopted for the implementation along with the algorithm design stage.

2.1. Strategeies adopted for implementation

The*primary* implementation strategy of the proposed system is that there should be increased number of information associated with the input of brain MRI image with more number of information being extracted in each stage discretely. The *secondary* implementation strategy is to ensure series of segmentation process to be carried out with efficient indexing process on both foreground and background image in order to ensure better classification results. The tertiary implementation strategy is to apply Artificial Neural Network over the statistically extracted featured from all the series of operation being carried out over the input brain MRI image for more precise in classification results.

2.2. Algorithm design

The proposed system consists of 4 essential set of operation to ensure successful classification of the abnormalities for a given input of brain MRI image. The brief discussions of the algorithms involved in the proposed system are as follows:

Processing input image: The system takes the input image of brain MRI followed by digitization of it in order to retain in the form of Matrix. This stage of operation also converts the input image to grayscale for easing the further processing steps. Once the grayscale input image is considered than it is subject next process for obtaining intensity variation vector after a two dimensional filter is constructed. A multi-dimensional image filtering process is applied on the grayscale image to obtain two dimensional vectors which is further used for constructing intensity variation vector. The obtained vector is than subjected to topographic mapping transformation which represents the input grayscale image in the form of topographical map where information about the brightness as well as ridges of the image is obtained. This process is the beginning of primary segmentation process which is capable of identifying the regions with primary possibility of tumor. Another advantage of this transformation process is that it colors all the significant regions differently to classify different regions of abnormalities. The steps of the algorithm are as follows:

Algorithm for Performing Initial Processing
Input: I (brain MRI)
Output: β (initial segmented image)
Start
1. (a, b)→f(I, α'), where α'= [α αT]
2. ivv→$\sqrt{}$(a^2+b^2)
3. β=ind(g(ivv))
End

The algorithm takes the input of I (brain MRI) which after processing leads to generation of β (initial segmented image). In this case, a function *f*(x) is used for controlling intensity variation vector (ivv) with respect to construction of an edge-defining filters α', where α' represents a matrix storing two dimensional filters (a, b) of *I* with respect to edge-defining filter α and transpose of it αT (Line-1). Therefore, *ivv* is obtained by using sqared sum expression used in Line-2. The next process is to obtain indexing by using function *ind* over *ivv* values obtained in prior step using another sub-function topological mapping transformation *g*(x).

Segmenting the image: Different from any existing segmentation approach, the proposed system performs very different series of approaches which actually complements the segmentation process for better classification performance. For that purpose, the system constructs elements of morphological structure with a shape of disk which will accelerate the process of dilation and erosion in morphological operation. Basically such elements are a two dimensional matrix with neighboring elements of binary value which is meant for considering the *true* pixel while discarding the *false* pixel elements. A reference pixel which is at the center is considered to carry out identification of *true* and *false* pixels. Such forms of segmentation are possible for both binarized as well as grayscale brain MRI images. This operation results in generation of mapped version of input image as well as morphed eroded image. The obtained morphed eroded image is then subjected to reconstruction process with respect to grayscale input image. Finally, the operation results in marking of the foreground image and elimination of the dark spots to remove any possibilities of outliers. The morphological operation is further continued by performing morphological dilation operation over the reconstructed image with respect to the structural elements from the prior processing steps. The obtained dilated image is now subjected to image reconstruction process followed by computation of the complement of recently obtained dilated image. This operation results in transforming the darker region of brain MRI image into lighter one while the lighter region of brain MRI image into darker one. Finally, the maximum region is obtained for assisting the segmentation process.

Algorithm for Segmenting Image
Input: I (brain MRI)
Output: Iseg (Segmented Image)
Start:
1. $m_1 \rightarrow mf_1(I^{\chi})$
2. $m_2 \rightarrow mf_2(I^{\chi})$
3. $m_3 \rightarrow m_\theta(m_2, I)$
4. $sr \rightarrow m_1(^{\chi})$
5. $m_5 \rightarrow mf_4(m_\theta(mf_4(mf_4, m_3)))$
6. $I_{seg} \rightarrow arg_{max}(m_5)$
End

The above algorithm takes the input of I (brain MRI) to give an outcome of I_{seg} (Segmented Image). The first process of this algorithm is to apply a function $mf_1(x)$ over image I with respect to morphological structural element χ (Line-1) to obtained input image (m_1). The second process is to obtain the eroded version (m_2) of the input image using morphological erosion function $mf_2(x)$ (Line-2). The third process is to perform reconstruction of the morphological image using fuction m_θ applied on m_2 and I (Line-3). The fourth operation is to remove the outliers of spots by considering m1 with respect to χ (Line-4). The fifth process is to apply a function $mf_4(x)$ for obtaining the image compliment with respect to reconstruction image using $m_\theta(x)$ function over compliment image of dilated version of outcome obtained from mf_4 and m_3 (Line-5). Finally, maximum region of such image i.e. m5 is considered as prominent abnormal region and is therefore segmented I_{seg} (Line-6).

Initiating the classification process: The next process is to apply the image binarization process to the recently obtained compliment image with respect to the gray thresholding of it. The obtained binarized matrix is now subjected to the computation process for obtaining the Euclidean distance between the binary images obtained. Further, the initial segmentation process using topographic mapping transformation is applied on the binarized image to further obtained more segmented image and thereby this process assists in marking the background. For better classification process it is necessary to control the intensity factor too at the end process. This process alters the image intensity with an aid of reconstruction of morphological elements with respect to obtained intensity variation vector and concatenation of marked background and compliment image. The obtained segmented image is than further subjected to topographic mapping transform. This process results in further segmentation process thereby offering better classified outcomes. The next step of this process is to apply finite directed graph without a form of involvement of cycles and with more inclusion of edges and vertex for better classification assistance. This process is further followed by constructing a believe network which is used for facilitating the decision making process in the presence of various variable sequences. As all the variables are encoded in the belief network therefore it can successfully control any form of missing data. Another advantage of this process is that it assists in good prediction over statistical data. This process is followed up by obtaining the entire region corresponding to the belief network followed by applying histogram on the top of it to perform region appending operation.

Algorthm for Initiating Classification
Input: m5 (segmented region)
Output: C1 (Classified Segmented region)
Start
1. $I_{bin} \rightarrow f_2(m_5, f_3(m_5))$
2. $\gamma_1 \rightarrow g(spat(I_{bin}))$
3. $\gamma = (\gamma_1 = =0)$
4. $I_{seg2} \rightarrow g_1(minima(f, \gamma | I_{seg}))$
5. $C \rightarrow [C1, C2, C3]^{\beta}$
6. $C_1 \rightarrow$ merge region (C)
End

The algorithm takes the input of m_5 (segmented region) which provides the outcome of *C* (Classified Segmented region). The initial step is to obtain the binarized image I_{bin} using function $f_2(x)$ over priorly obtained morphological elements m_5 and graythresholded version of m_5 (Line-1). The next step is to obtain the spatial distance between the elements in binarized image I_{bin} following by applying similar function g(x) for topographic mapping transformation to obtained binarized transformed image γ_1 (Line-2). The indexing of the background is then followed (Line-3). The next part of the implementation is about performing segmentation using similar topographic mapping transformation process. For this purpose, the minima of the image is obtained considering ivv values and concatenation of obtained γ and Iseg that is extracted in prior algorithmic step (Line-4). This operation gives second version of the segmented image I_{seg2} (Line-4). The algorithm then applies finite directed graph, believe network, and histogram considering labels of the region β in order to obtained primary classified image C (Line-5). Finally, a region merging is carried out over C in order to obtained finally classified and segmented region (Line-6).

Boosting classification using artificial neural network: The proposed system doesn't directly apply Artificial Neural Network but it chooses to incorporate precise inputs to the neuron before starting training operation. For this purpose, the proposed system carries out feature extraction process where all the statistical features can be predicted. The proposed system uses all the frequently used descriptive statistical parameters over the brain MRI image for computing the features. Incorporating artificial Neural Network offers significant advantage in terms of extracting the inference from the large set of data as well as vague data. Therefore, better pattern extraction as well as identification of significant trends can be investigated. Therefore, the obtained information can be used for constructing an information structure using Artificial Neural Network. Such newly formulated structure comprises of massive quantity of highly interconnected elements in order to solve classification problem. The training operation is carried out by considering the prior steps of input image processing, segmentation, and initial classification operation. The proposed system uses real-valued function in order to construct an activation function in Artificial Neural Network. This adoption of training method offers various benefits e.g. forecasting of time-series as well as function approximation. This training operation involves iterating the learning process till elite classification information is obtained by the process. Finally, after the completion of the training operation, the proposed system can successfully perform classification that if the obtained image has presence of tumor or there is absence of tumors. Therefore, an effective classification process is obtained and a precise classification process is obtained.

Algorithm for classification using artificial neural network
Input: Ihist (image histogram), C1 (directed graph), C2 (belief network), β (index)
Output: Flag (classification of brain abnormality)
Start
1. **For** i=1: C1
2. Calculate Cdist(Ihist, length(C1)
3. **End**
4. Apply merge region(C1, C2, β)
5. Obtain Fv(stat)→I(β)
6. Apply ANN(Fv)
7. **If** (class(i)==2)
8. Flag Malignant
9. **Else**
10. Flag benign
End

For all directed graph (C1), the algorithm obtains the correlated distance C_{dist} with respect to image histogram I_{hist} (Line-1). A statistical feature vector Fv is obtained (Line-5) followed by applying Artificial Neural Network (Line-6). Depending upon the region class, the algorithm makes a binary decision of malignancy or benign stage of abnormality of the brain tumor. The proposed system obtains highly precisive classified image in this process.

3. RESULTS AND ANALYSIS

From the discussion made by the prior section, it is clear that there are various sequential steps implemented toward novel segmentation process mainly for assisting the classification of the abnormalities in brain MRI. Scripted in MATLAB, the proposed system targets assessing the classification performance of brain MRI image. Following are the brief of database used, result analysis strategy, visual outcomes, and numerical outcomes.

3.1. Database used

Majority of the MRI images are greyscaled and there are various availability of the brain MRI dataset publically. Therefore, there is good availability of the brain MRI dataset for carrying out the proposed analysis of classification. Hence, the analysis is carried out using an input image to be brain MRI data sourced from publically available standard dataset [30]. The dataset consist of brain MRI data of more than

1000 subjects with 2168 sessions of magnetic resonance, and 1608 Positron Emission Tomography session. The dataset were captured considering various clinical test state for the subject. The proposed study has been tested with more than 5000 brain MRI data with variable sizes of the data. The dataset is also accompanied by the ground truth value for the purpose of the model validation.

3.2. Analysis strategy

As the proposed study aims for addressing classification problems considering the case study of brain MRI image, therefore, accuracy is the primary performance parameters considered for the analysis. Apart from accuracy, the proposed study is also assessed considering processing time for the classification process. This adoption will also ensure analysis of the complexity involved in the learning process.

3.3. Visual results

The visual outcomes of the proposed system for one sample brain MRI image are shown in Figure 2. After taking the input image Figure 2(a), Intensity Variation Vector (IVV) (as shown in Figure 2(b) is obtained followed by obtaining image for Topographic Mapping transformation (TMT) as shown in Figure 2(c). The foreground in indexed Figure 2(d) followed by elimination of the dark spots Figure 2(e) for resisting outliers followed by clearing all the edges Figure 2(f), Figure 2(g), and Figure 2(h).

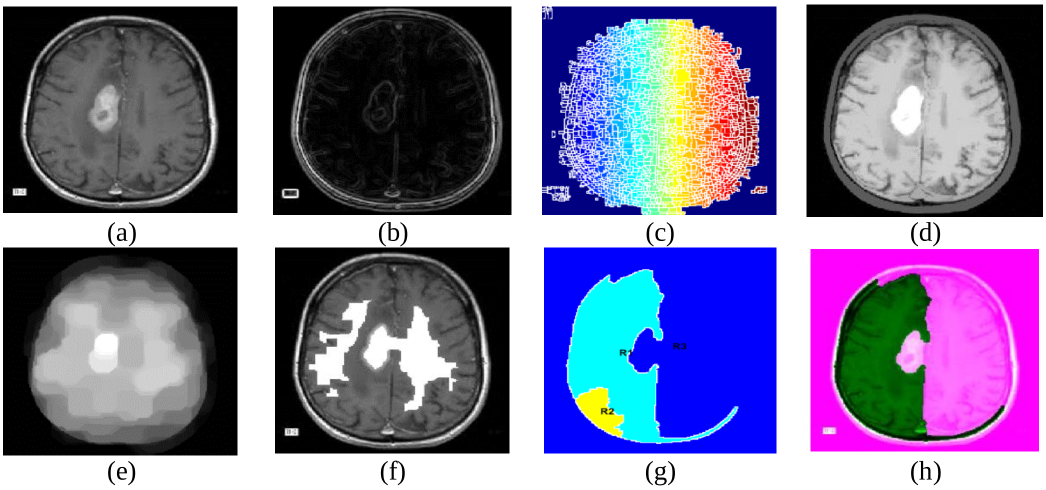

Figure 2. Visual outcomes; (a) Input image, (b) IVV, (c) TMT, (d) Indexing foreground, (e) Elimination of dark spots, (f) Clearance of edges, (g) TMT segmentation, (g) TMT segmentation

This process is followed by TMT-based segmentation process which offers a comprehensive color based classification over the discrete regions of brain MRI image Figure 2(g)) and this operation is also followed by indexing different regions with specific index in numbers. Finally, after applying training using Artificial Neural Network, the proposed system performs identification of the tumor region as well as predicts if the tumor is malignant or benign.

3.4. Numerical results

In order to evaluate the effectiveness of the proposed system, the outcomes of it are compared with the other approaches of training e.g. support vector machine, self-organizing map, feed-forward, etc. Similar set of images (set of images with abnormalities of tumor and normal regions) are considered for comparative analysis. The study also considers various parameters for computing accuracy e.g. True Positive, True Negative, False Positive, False Negative, Sensitivity/Recall Rate, Specificity, Precision, F1-Score, etc.

The analysis shown in Figure 3 and Figure 4 is carried out considering standard dataset [30] only. From the outcome, it can be seen that proposed system offers better accuracy score as seen the precision and F1-score values. The complete processing time of the algorithm is found to be 0.28871 seconds while the range of processing time of existing system varies between 0.42883-1.6883 seconds. The overall accuracy of the proposed system is found to be approximately 99% in contrast to the existing training approaches. It can be also seen that proposed system offers highly reduced false positive in contrast to the existing system. The prime reason behind this the comprehensive classification process that leads to better form of feature extraction process. Hence, it can be seen that adopted artificial neural network has a significant positive impact on the classification performance for brain MRI image irrespective of the type and complexity present within the image. Apart from this, there is no buffer stored as the complete process works on run-time stating negligibly less spatial complexity.

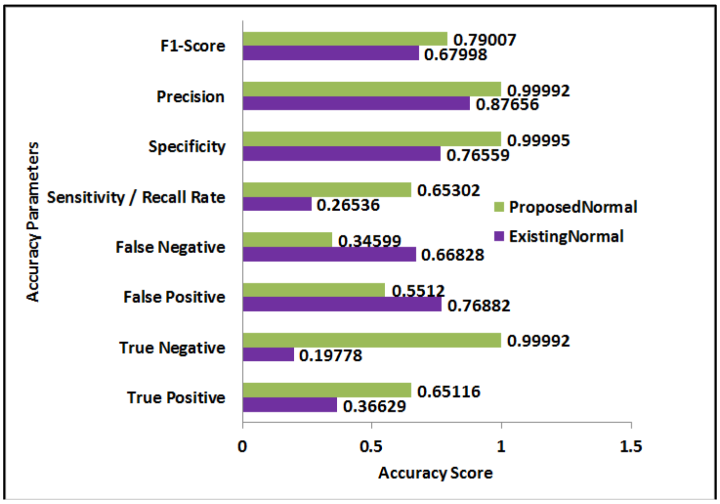

Figure 3. Comparative analysis of accuracy for normal regions in brain MRI

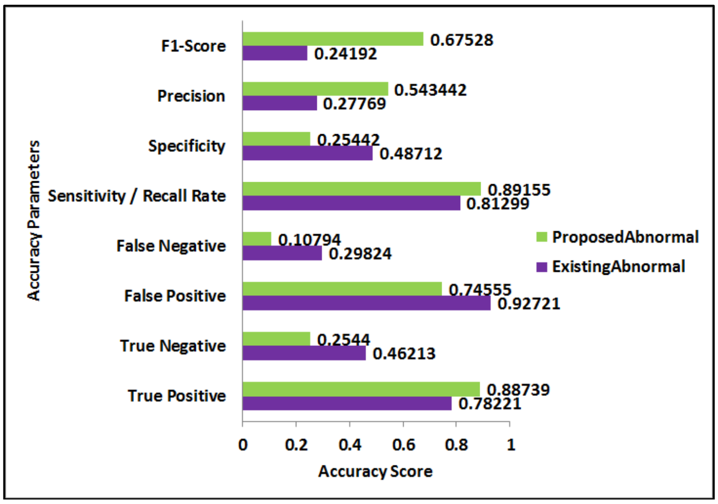

Figure 4. Comparative analysis of accuracy for abnormal regions in brain MRI

4. CONCLUSION

This paper discusses that classification is one of the essential operation in medical image processing. In complicated clinical diagnosis of brain MRI, it is required that maximum information being retrieved in the operation prior to applying classification operation. In this regards, segmentation plays a big role. Different from conventional segmentation process, the proposed system has introduced a novel segmentation process carried out in multiple steps that mainly uses topographic mapping transformation. This mechanism lets the segmentation to be carried out on smaller segment of region with specific pixel information from the input brain MRI. The system also uses morphological operation followed by applying graph theory and believe network for further assisting in better decision making process. Finally, neural network is applied for boosting the training performance where the final outcome of proposed system is found to be offer approximately 99% of accuracy.The proposed segementation and classification model can be considered for different set of brain tumor datasets, different types of tumor detection. Also, the computation time of segementation and classification can be consideref in future line of research.

REFERENCES

[1] Nilanjan Dey, Amira Salah Ashour, Fuquian Shi, Valentina E. Balas, *Soft Computing Based Medical Image Analysis*, Academic Press, 2018.
[2] N. Varuna Shree, T. N. R. Kumar, "Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network," *Springer, Brain Informatics*, vol. 5, no. 1, pp. 23-30, 2018
[3] Luigi Landini, Vincenzo Positano, Maria Santarelli, *Advanced Image Processing in Magnetic Resonance Imaging*, CRC Press, 2018.
[4] Zhe Xiao, Yi Ding, Tian Lan, Cong Zhang, Chuanji Luo, and Zhiguang Qin, "Brain MR Image Classification for Alzheimer's Disease Diagnosis Based on Multifeature Fusion," *Hindawi-Computational and Mathematical Methods in Medicine*, vol. 2017 , pp. 1-13, 2017.
[5] Hiroyuki Sugimori, "Classification of Computed Tomography Images in Different Slice Positions Using Deep Learning," *Hindawi-Journal of Healthcare Engineering*, vol. 2018, pp. 1-9, 2018.
[6] Ivana Despotović, Bart Goossens, and Wilfried Philips, "MRI Segmentation of the Human Brain: Challenges, Methods, and Applications," *Hindawi-Computational and Mathematical Methods in Medicine*, vol. 2015, pp. 1-23, 2015.
[7] Liu, Jin, Li, Min, Wang, Jianxin, Wu, Fangxiang, Liu, Tianming, Pan, Yi, "A Survey of MRI-Based Brain Tumor Segmentation Methods," *Tsinghua Science and Technology*, vol. 19, pp. 578-595, 2014.
[8] Reshma Hiralal, Hema P Menon, "A Survey of Brain MRI Image Segmentation Methods and the Issues Involved," *Springer-The International Symposium on Intelligent Systems Technologies and Applications*, pp. 245-259, 2016.
[9] Liu, Jin, Li, Min, Wang, Jianxin, Wu, Fangxiang, Liu, Tianming and Pan, Yi, "A Survey of MRI-Based Brain Tumor Segmentation Methods, *Tsinghua Science and Technology*, vol. 19, pp. 578-595, 2014.
[10] S. Harish, G. F. A. Ahammed and R. Banu, "An extensive research survey on brain MRI enhancement, segmentation and classification," *2017 International Conference on Electrical, Electronics, Communication, Computer, and Optimization Techniques (ICEECCOT)*, Mysuru, pp. 1-8, 2017.
[11] J. Huang *et al*., "Identifying Resting-State Multi frequency Biomarkers via Tree-Guided Group Sparse Learning for Schizophrenia Classification," in *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 1, pp. 342-350, Jan. 2019.
[12] A. Kermi, K. Andjouh and F. Zidane, "Fully automated brain tumour segmentation system in 3D-MRI using symmetry analysis of brain and level sets," in *IET Image Processing*, vol. 12, no. 11, pp. 1964-1971, 2018.
[13] C. Ma, G. Luo and K. Wang, "Concatenated and Connected Random Forests With Multiscale Patch Driven Active Contour Model for Automated Brain Tumor Segmentation of MR Images," in *IEEE Transactions on Medical Imaging*, vol. 37, no. 8, pp. 1943-1954, Aug. 2018.
[14] Z. Wang, Y. Zheng, D. C. Zhu, A. C. Bozoki and T. Li, "Classification of Alzheimer's Disease, Mild Cognitive Impairment and Normal Control Subjects Using Resting-State fMRI Based Network Connectivity Analysis," in *IEEE Journal of Translational Engineering in Health and Medicine*, vol. 6, pp. 1-9, 2018.
[15] L. Yuan, X. Wei, H. Shen, L. Zeng and D. Hu, "Multi-Center Brain Imaging Classification Using a Novel 3D CNN Approach," in *IEEE Access*, vol. 6, pp. 49925-49934, 2018.
[16] T. Zhan *et al*., "A Glioma Segmentation Method Using CoTraining and Superpixel-Based Spatial and Clinical Constraints," in *IEEE Access*, vol. 6, pp. 57113-57122, 2018.
[17] A. Gumaei, M.M. Hassan, M.R. Hassan, A. Alelaiwi and G. Fortino, "A Hybrid Feature Extraction Method With Regularized Extreme Learning Machine for Brain Tumor Classification," in *IEEE Access*, vol. 7, pp. 36266-36273, 2019.
[18] Y. Liu, Y. Wei and C. Wang, "Subcortical Brain Segmentation Based on Atlas Registration and Linearized Kernel Sparse Representative Classifier," in *IEEE Access*, vol. 7, pp. 31547-31557, 2019.
[19] M. Wang *et al*., "Graph-Kernel Based Structured Feature Selection for Brain Disease Classification Using Functional Connectivity Networks," in *IEEE Access*, vol. 7, pp. 35001-35011, 2019.
[20] J. Liu, M. Li, Y. Pan, F. Wu, X. Chen and J. Wang, "Classification of Schizophrenia Based on Individual Hierarchical Brain Networks Constructed From Structural MRI Images," in *IEEE Transactions on NanoBioscience*, vol. 16, no. 7, pp. 600-608, Oct. 2017.
[21] T. Kaur, B. S. Saini and S. Gupta, "Quantitative metric for MR brain tumour grade classification using sample space density measure of analytic intrinsic mode function representation," in *IET Image Processing*, vol. 11, no. 8, pp. 620-632, 2017.
[22] N. K. Kasabov, M. G. Doborjeh and Z. G. Doborjeh, "Mapping, Learning, Visualization, Classification, and Understanding of fMRI Data in the NeuCube Evolving Spatiotemporal Data Machine of Spiking Neural Networks," in *IEEE Transactions on Neural Networks and Learning Systems*, vol. 28, no. 4, pp. 887-899, Apr. 2017.
[23] N. Kasabov, L. Zhou, M. Gholami Doborjeh, Z. Gholami Doborjeh and J. Yang, "New Algorithms for Encoding, Learning and Classification of fMRI Data in a Spiking Neural Network Architecture: A Case on Modeling and Understanding of Dynamic Cognitive Processes," in *IEEE Transactions on Cognitive and Developmental Systems*, vol. 9, no. 4, pp. 293-303, Dec. 2017.
[24] R. Armañanzas, M. Iglesias, D. A. Morales and L. Alonso-Nanclares, "Voxel-Based Diagnosis of Alzheimer's Disease Using Classifier Ensembles," in *IEEE Journal of Biomedical and Health Informatics*, vol. 21, no. 3, pp. 778-784, May 2017.
[25] J. Liu, M. Li, W. Lan, F. Wu, Y. Pan and J. Wang, "Classification of Alzheimer's Disease Using Whole Brain Hierarchical Network," in *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 15, no. 2, pp. 624-632, 2018.
[26] M. Liu, J. Zhang, E. Adeli and D. Shen, "Joint Classification and Regression via Deep Multi-Task Multi-Channel Learning for Alzheimer's Disease Diagnosis," in *IEEE Transactions on Biomedical Engineering*, vol. 66, no. 5, pp. 1195-1206, May 2019.

[27] P. Kumar Mallick, S. H. Ryu, S. K. Satapathy, S. Mishra, G. N. Nguyen and P. Tiwari, "Brain MRI Image Classification for Cancer Detection Using Deep Wavelet Autoencoder-Based Deep Neural Network," in *IEEE Access*, vol. 7, pp. 46278-46287, 2019.

[28] Y. Shao, J. Kim, Y. Gao, Q. Wang, W. Lin and D. Shen, "Hippocampal Segmentation From Longitudinal Infant Brain MR Images via Classification-Guided Boundary Regression," in *IEEE Access*, vol. 7, pp. 33728-33740, 2019.

[29] L. Wang, C. Xie and N. Zeng, "RP-Net: A 3D Convolutional Neural Network for Brain Segmentation From Magnetic Resonance Imaging," in *IEEE Access*, vol. 7, pp. 39670-39679, 2019.

[30] A. Gudigar, U. Raghavendra, E. J. Ciaccio, N. Arunkumar, E. Abdulhay and U. R. Acharya, "Automated Categorization of Multi-Class Brain Abnormalities Using Decomposition Techniques With MRI Images: A Comparative Study," in *IEEE Access*, vol. 7, pp. 28498-28509, 2019.

[31] "OPenfmri", [Online] Available: https://openfmri.org/dataset/, [Retrieved on 13-06-2019].

BIOGRAPHIES OF AUTHORS

Harish S., I have completed B.E. in Telecommunication Engineering from Bangalore University, and M. Tech in Information & Communication Systems from Visvesvaraya Technological University. Pursuing Ph. D in Electrical Engineering from Visvesvaraya Technological University. I am having 13 years of teaching experience. My area of research is Bio-medical Image Processing. Currently working as Associate Professor in RL Jalappa Institute of Technology, Doddaballapur, India

Dr. G. F. Ali Ahammed working as an Associate Professor & HOD in the Department of Digital Electronics &Communication systems at VTU PG centre, Mysuru. He is having 15 years of Teaching and Research Experience. He pursued Ph.D., Computer Science & Technology, from Sri Krishna Devaraya University, Anantapur, Andra Pradesh. Master of Technology, Networking & Internet Engineering, from Visvesvaraya Technological University, Belagavi, Bachelor of Engineering in Electronics & Communication Engineering, from Bangalore University, Bangalore. He worked as BOE member for Visvesvaraya Technological University, Belagavi. He is also BOE member for SJCE Mysore & NIE Mysore, Autonomous Colleges. He is BOS member for NIE Autonomous college. He is Local Inspection Committee (LIC) member for VTU, Belagavi. He has published several Research papers in International, National Journals/conferences. He is a Member of CSI, IAENG, IBM Academic Initiative, and LM ISTE. Dr. G.F. Ali Ahammed area of interest and research include Networking, Performance enhancement algorithms, Cloud Computing, cryptography and Communication. He has the Recipient of Seed money Young Scientist Research Award (SMYSR) from Vision Group of Science and Technology (VGST), Bangalore. He is also fetched various Grants from VGST&AICTE.